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Neural network modelling for the analysis of forcings/temperatures relationships at different scales in the climate system

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Abstract

A fully non-linear analysis of forcing influences on temperatures is performed in the climate system by means of neural network modelling. Two case studies are investigated, in order to establish the main factors that drove the temperature behaviour at both global and regional scales in the last 140 years. In particular, our neural network model shows the ability to catch non-linear relationships among these variables and to reconstruct temperature records with a high degree of accuracy. In this framework, we clearly show the need of including anthropogenic inputs for explaining the temperature behaviour at global scale and recognise the role of El Niño southern oscillation for catching the inter-annual variability of temperature data. Furthermore, we analyse the relative influence of global forcing and a regional circulation pattern in determining the winter temperatures in Central England, showing that the North Atlantic oscillation represents the driven element in this case study. Our modelling activity and results can be very useful for simple assessments of relationships in the complex climate system and for identifying the fundamental elements leading to a successful downscaling of atmosphere–ocean general circulation models.

Keywords: Neural network; Climate change; Forcing; Circulation pattern

1. Introduction

It is well known that atmosphere–ocean general circulation models (AOGCMs) are the standard tools for grasping the complexity of climate system and simulating its behaviour, in the past as well as in future scenarios. In particular, they allow us to reconstruct and forecast the climate at large scale.

By means of AOGCMs, we can use our theoretical description of the single main phenomena and processes in the climate system, put them together in a system of equations and parametrisation routines and dynamically reconstruct the simplified behaviour of this complex system in a computer, that can be seen as a virtual laboratory. In this context, we are able to recognise the role of some cause–effect relationships and to relate them with the underlying causes of the major changes in the behaviour of some important variables, like the annual global temperature (Houghton et al., 2001).

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Nevertheless, this dynamical approach also shows some limits in the simulations at regional and local scales and, at a more fundamental stage, in the delicate balance among the relative strength of feedbacks and the various parametrisation routines, which can crucially affect the results of AOGCMs.

In this framework, a non-dynamical approach, which is able to catch non-linear relationships among several variables in the climate system, can be useful in order to perform an independent analysis of influence/causality, to "weight" the magnitude of different causes on a single effect (like the temperature variations) and to assess the relative importance of global forcings and regional circulation patterns, even on regional mean variables.

The simplest non-dynamical approach is surely given by the application of a multivariate linear regression model (forcings versus temperature) in the attempt at understanding the amount of variance explained by the various forcings in the reconstruction of temperature records. But, as we will see, a linear model is too simple to catch the complex non-linear behaviour of the temperature. So, in this situation, a neural network model could be useful, due to its characteristic features of a multivariate non-linear regression model that can be seen as a global correlative law-finder.

Recently, neural network models were specifically developed and applied to particular problems in atmospheric and climate sciences, namely in boundary layer short range forecasting (Pasini and Ameli, 2003), El Niño prediction (Tangang et al., 1998) and AOGCMs downscaling (Snell et al., 2000). Here, we adopt this neural strategy and concentrate on two case studies in which we can analyse the influence of natural/anthropogenic forcings and circulation patterns on the temperature behaviour at global and regional scales.

At our knowledge, a similar neural approach has been followed in the past only by Walter et al. (1998) and Walter and Schönwiese (2002). However, our present attempt is quite different from their investigation, for several reasons. First of all, we develop and apply a neural network model endowed with some well founded peculiarities, like the presence of a momentum term in the backpropagation training rule, the application of a so-called "all frame" training, to be discussed in Section 3, and a network topology characterised by few hidden neurons for short time series analysis. Furthermore, while in Walter et al. (1998) and Walter and Schönwiese (2002) the authors' attention was devoted almost completely to attribution and detection of anthropogenic climate change; here, we discuss the role of both natural and anthropogenic forcings, together with the peculiar contributions of El Niño southern oscillation (ENSO) and the North Atlantic oscillation (NAO) to the temperature behaviour at global and regional scales, by using real time series as references. Finally, the present paper is an improvement of previous analyses (Pasini et al., 2003b).

In what follows we will present the data available in literature and in web sites (Section 2) and our neural network model (Section 3). In Section 4, an influence analysis of physical–chemical forcings and ENSO on the behaviour of annual global temperature will be performed. In Section 5, a regional case study, related to the influence of global forcings and the NAO phenomenon on the temperature time pattern in an English region, will be presented. Finally, we will draw brief conclusions and discuss about further possible work.

2. Data

At present, in both recent papers and web sites a lot of quantitative information is available about global/regional meteorological parameters and indices, as well as data about physical–chemical forcings to the climate system. Here, we deal with the following data:

- Global temperature anomalies since 1856 (from http://www.cru.uea.ac.uk).
- Central England temperatures (CET) since 1659 (from http://www.badc.nerc.ac.uk/data/cet). These monthly mean temperatures are representative of a roughly triangular area of the United Kingdom enclosed by Preston, London and Bristol.
- Solar irradiance anomalies, representative of the solar activity, since 1700 (from Hoyt and Schatten (1993) and http://daac.gsfc.nasa.gov).
- Stratospheric aerosol optical thickness at 550 nm since 1850 (from Sato et al. (1993) and http://www.giss.nasa.gov/data/strataer): this series is representative of the past volcanic activity in terms of the optical properties of low stratosphere.
- Global concentration of carbon dioxide (CO_2) since 1860 (from http://cdiac.esd.ornl.gov).

- Emissions of sulfates (SO_x) at global level since 1850 (from http://www.rpi.edu/~sternd/datasite.html).
- Southern oscillation index (SOI), related to ENSO, since 1866 (from http://www.cru.uea.ac.uk).
- Monthly NAO index since 1821 (from http://www.cru.uea.ac.uk).

Hereafter, we will consider solar irradiance and stratospheric optical thickness as indices of natural forcings to the climate system, while CO_2 concentration and sulfate emissions will be considered as anthropogenic forcings.

In what follows, our idea is to analyse the influence of these forcings and of the circulation patterns on the available series of temperatures, in order to understand which of them are the most important so to allow us to reconstruct the temperature records at global and regional scales. In doing so, we apply a neural network model, that will be briefly described in the next section.

3. Neural network model

A neural network development environment, characterised by some original features, has been created some years ago (Pasini and Potestà, 1995). Its models and training facilities have been progressively applied to short-range prognostic problems in the boundary layer (Pasini and Potestà, 1995; Pasini et al., 2001, 2003a; Pasini and Ameli, 2003). Recently, also a preliminary attempt at analysing climatic data has been performed by the same tool (Pasini et al., 2003b).

The neural networks considered in the present study are feed-forward and trained by means of a backpropagation strategy. We use a generalised Widrow–Hoff rule for updating the connection weights that is characterised by the presence of both gradient descent and momentum terms (Pasini and Potestà, 1995). A particular attention is paid to the form of sigmoids, which represent our neural transfer functions: therein, the arguments of the exponential function are normalised with respect to the number of connections converging to a single neuron of the input and hidden layer, respectively, as sketched in Pasini et al. (2001). A discussion about this choice and its advantages, together with practical examples of application, can be found in Pasini et al. (2003a). Finally, an early stopping method is also used in order to prevent overfitting.

As far as the topology of our neural networks is concerned, we stress that it is driven by the peculiar problem we handle with. In particular, we aim at performing a multivariate non-linear regression by neural modelling in order to understand the possible influence role of forcings and circulation patterns (inputs) in the determination of a record of temperature at a global or regional scale (target). Thus, in the following we consider networks characterised by up to five inputs and one output; furthermore, we deal with few (four or five) hidden neurons in a single hidden layer: this allows us to obtain a good representation of the underlying function without falling down into any kind of overfitting.

Once trained, the neural network is nothing but a function that maps input patterns to values of temperature at the same time, thus representing a fully non-linear diagnostic correlative law, which links together a set of inputs (physical–chemical variables and circulation patterns) and the values of temperature forced by them. However, due to the non-linear nature of network regression, a neural model would be able to exactly mimic the target values without extracting any correlation law if the correspondent inputs–target patterns are included in the training set and a sufficiently large number of hidden neurons were allowed. Thus, in order to discover the physical relationship between inputs and targets, we exclude some inputs–target pair from the training set on which we build the correlative law. Once trained the network, we use the excluded pairs as a validation/test set in order to assess the modelling performance on new cases that are unknown to the network.

Due to the limited statistics available (about 140 inputs–target patterns for each case study), every temperature value is estimated at a time after the exclusion of the correspondent inputs–target pattern from the training set used for fixing the connection weights. Here, we use a facility of our tool, the so-called “all frame” training procedure: it is simply sketched in Fig. 1, where our total set of patterns is divided in two subsets. The white squares represent the elements (patterns) of our training set, while the gray square (one single element) represents the test set. The relative compositions of training and test sets change at each step of an iterative procedure of training + test cycles.

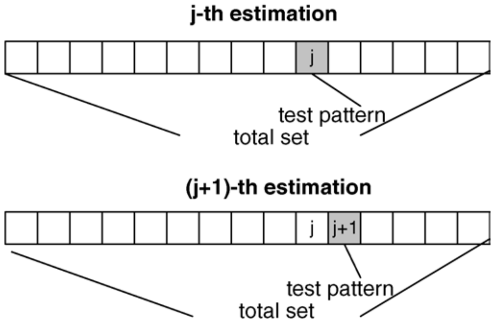

Fig. 1. Sketch of the iterative procedure called “all frame” training.

A “hole” in the complete set represents our test set and moves across this total set of patterns, thus permitting the estimation of all temperature values at the end of the procedure.

4. An influence analysis at global scale

In this first case study at global level, we would like to estimate the influence of natural/anthropogenic forcings and ENSO on the behaviour of annual global mean temperature since 1866. As already cited in Section 2, here we consider solar irradiance and stratospheric optical depth as indices of natural forcings on the climate system, while CO_2 concentration and sulfate emissions, mainly due to manmade activities, are seen as anthropogenic forcings. Furthermore, also data about the ENSO phenomenon are included in this analysis, because the large amount of ocean surface affected by the oscillation between warming and cooling periods and recognised ENSO teleconnections with other regions of the world (see, for instance, Brönniman et al. (2004)) could contribute to determine the value of annual mean temperature over the world.

The first preliminary aim of our investigation is to assess the non-linearities hidden in the climate system as represented by our data about physical–chemical forcings, an inter-connected ocean–atmosphere circulation pattern (ENSO) and temperature. For this reason, together with the application of a neural network model, we use a classical multivariate linear analysis, too. By these models, we want to achieve also our fundamental goal, the cited influence analysis, by finding the best linear and non-linear reconstructions of temperature time pattern in the following four cases, when the models themselves are fed by data about:

(a) natural forcings only;
(b) anthropogenic forcings only;
(c) natural + anthropogenic forcings;
(d) natural + anthropogenic forcings + ENSO.

In doing so, we adopt the “all frame” training procedure previously described, for both the neural model and the multi-linear regression. In the latter case, we estimate each annual temperature by means of the linear combination law obtained by the regression on the other forcings/temperature patterns of our sample. As well known, due to the use of a least-squares method in the linear regression, our “all frame” procedure could enhance the role of outliers in this case. For this reason, together with the classical multivariate linear regression, we perform also a “robust” linear regression endowed with distinct weights for the outliers themselves: anyway, the results are very similar and we can find differences only in the fourth decimal digit of the linear correlation coefficient.

The performance of linear and neural models in reconstructing the global annual temperature is presented in Table 1 in terms of the linear correlation coefficient R (observed T versus estimated T). Note that the error bars associated to the results of the neural network model come from ensemble runs (10 for each case) with different random initial weights, so that the networks are able to widely explore the landscapes of the cost functions: they indicate ±2 standard deviations.

With reference to Table 1, it is clear that the full non-linear method (neural networks) allows us to better reconstruct temperature in the last three cases, while the relationship between natural forcings and temperature is probably characterised by a weak non-linear component which does not permit to overcome the linear performance. Furthermore, when anthropogenic

Table 1
Reconstruction performance in terms of the linear correlation coefficient R for this analysis at global scale (four case studies)

Input forcings	Linear model	Neural model
Natural	0.661	0.622 ± 0.014
Anthropogenic	0.818	0.847 ± 0.005
Natural + anthropogenic	0.828	0.852 ± 0.005
Natural + anthropogenic + ENSO	0.844	0.877 ± 0.004

forcings were taken into account, the increase in performance is statistically significant (outside the error bars). In these latter cases, a fully non-linear model shows its usefulness in catching non-linearities hidden in the data and in using them for exploring correlative laws that grasp just this non-linear influence of forcings on global temperature.

A more comprehensive analysis can be performed by looking at the specific time evolution of reconstructed temperature versus the observed temperature record. Even if we do not show the graphs related to the performance of linear correlation for lack of space, we can say that, in the case of linear and neural models fed by natural forcings only, a similar failure in reconstructing temperature is visible, while, in the other cases, we can appreciate the better performance obtained by neural modelling. Furthermore, in any of these latter cases, only a smooth trend is partially caught by the linear model, and no sign of inter-annual variability is shown by the reconstructed temperatures.

Now, with reference to Fig. 2, we analyse in more detail the results coming from the application of our neural network model to this global case study.

First of all, it is clear that taking only the natural inputs into account, we are not able to find a correlative law that explains the behaviour of global temperature. In particular, we find a very strong failure in the reconstruction during the period 1900–1960 and we can note difficulties even for the more recent warming of the last decade. Our result can be compared with an analogous

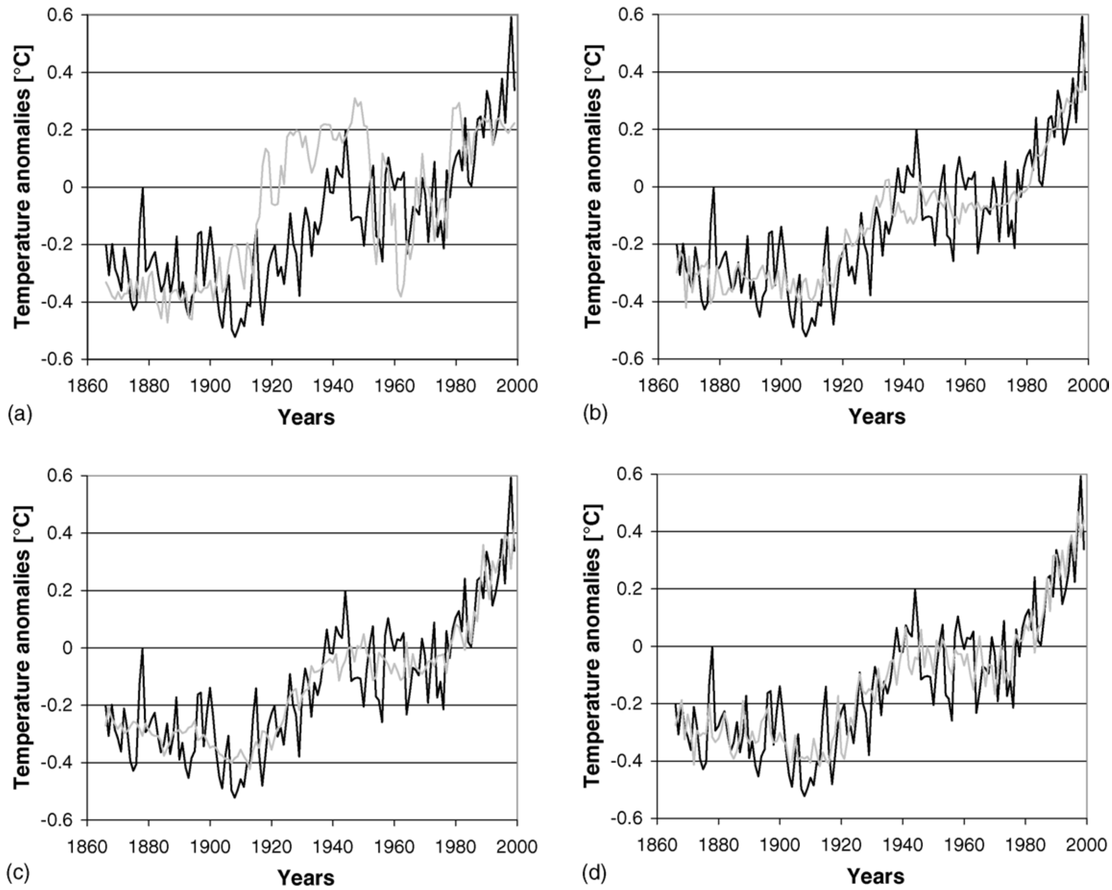

Fig. 2. Observed annual global temperature (black curve) vs. estimated annual global temperature by neural modelling (gray curve) when the networks have been trained by inputs related to: (a) natural forcings only; (b) anthropogenic forcings only; (c) natural + anthropogenic forcings; (d) natural + anthropogenic forcings + ENSO.

failure in reconstructing the global temperature record by application of ensemble runs of an AOGCM driven uniquely by observed variations of natural forcings in the past (Houghton et al., 2001). In that dynamical analysis a peculiar failure in reconstructing the warming of the last 40 years was found and this result (among many others) leads to consider the anthropogenic forcings as fundamental for reconstructing the global temperature of this recent period. In the present analysis, because of the nature of neural modelling (which can be defined as a globally correlative and non-dynamical method), our results cannot infer so precise conclusions, but substantially mean that our networks are not able to find a valid correlative law if fed by natural inputs only. Among the many correlative laws explored during the training phase (each of them is erroneous), the law finally found is simply the closer one to the target data.

In the second application of the neural model to our global problem, when two anthropogenic forcings are used to feed the network, we can appreciate a very evident increase in performance. In particular, the trend of global temperature is well recovered and some discrepancies can be only found in the too smooth form of the reconstructed temperature, which shows only weak traces of an inter-annual variability, in the overestimation of the absolute minimum and the underestimation of a relative maximum (around 1945) of the time series. Anyway, this result shows the need to consider the real variations of anthropogenic forcings if we want to reconstruct the annual global temperature. This hints that anthropogenic forcings can be fundamental causes of temperature variations during the period considered here.

The natural further step in our analysis is the introduction of data about both anthropogenic and natural forcings as inputs in our model. The joint use of these kinds of forcing leads to a very little increase in performance (within an error bars overlapping), if compared to the previous case (anthropogenic forcings only). In any case, now the amount of variance not explained by our model is almost completely due to the inter-annual variability.

Finally, we add an input neuron to the latter network topology in order to insert data about ENSO. The results presented in Table 1 and Fig. 2(d) show that we obtain a further quite consistent improvement in performance. In a certain sense, one could be led to say that ENSO acts as a second-order corrector to the estimation obtained by anthropogenic and natural forcings and leads to a better catching of inter-annual variability. Nevertheless, we can note that, of course, in a non-linear system we cannot separate the single contributions to the final result.

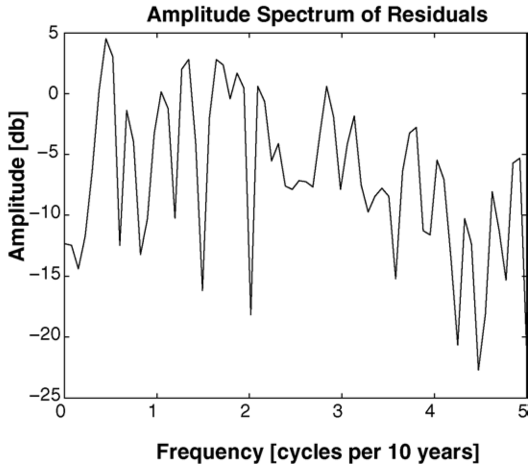

Fig. 3. Fourier spectrum of our residual time series.

As a partial conclusion, we can say that this analysis clearly shows a strong non-linear link between anthropogenic forcings and the temperature record of the period considered, so that these forcings can appear as the main probable causes of these changes. Furthermore, the joint use of anthropogenic/natural forcings and ENSO data leads to a very good reconstruction of our time series, so that we can advance the hypothesis that the variance not explained by our final model could be probably due (almost completely) to a natural variability of the climate system.

A simple way to possibly corroborate or falsify this last conjecture is to look at the structure of the residuals in order to understand if they appear as due to a random process or to some hidden dynamics coming from one or more neglected dynamical causes. As well known by statistics (see, for instance, von Storch and Zwiers (1999) for a general reference), a random process is linked to a white noise spectrum in the Fourier analysis and to an autocorrelation function (ACF) characterised by approximately null values (except the first one). In our case, even if such an analysis is obviously limited by the shortness of the sample available, however, some considerations can be done by looking at Figs. 3 and 4.

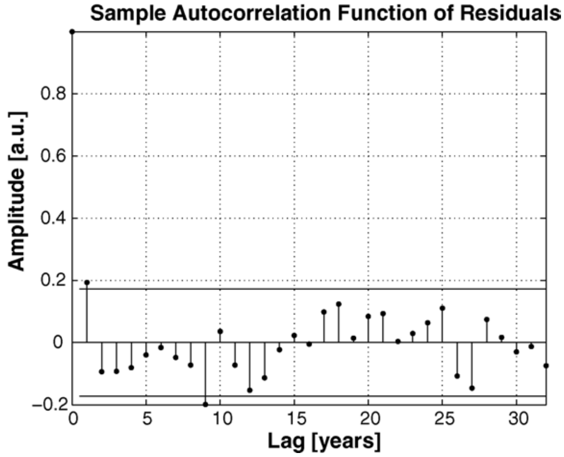

Fig. 4. Autocorrelation function of our residual time series.

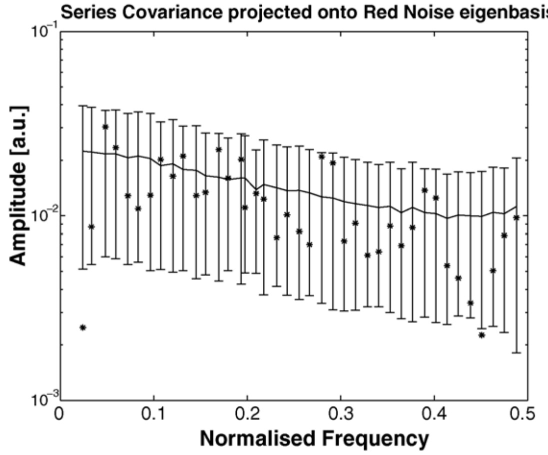

Fig. 5. MCSSA test against red noise.

First of all, the Fourier spectrum shows no particular peak and periodicity. On the other hand, the spectrum trend is almost flat, but some decrease in the amplitude is visible when frequency increases above three cycles per 10 years, so that a hypothesis of red or pink noise can be alternative to that of white noise. Really, we have not enough data to support one of these hypotheses.

Looking at Fig. 4, we see that the autocorrelation function is almost completely confined inside the lines, which determine the limits for white noise. Furthermore, some oscillations are visible in the graph, but these are more uncoupled than in results of previous studies (see Walter and Schönwiese (2002) for an example of ACF application to an analogous problem).

As a matter of fact, no undoubted conclusion can be reached by the analysis of Fourier spectrum and ACF. Here, the main difficulty is due to the shortness of our time series of residuals. Furthermore, these methods can allow us to discriminate between white noise and periodic/dynamic signals, while in geophysical time series the most frequent feature is the fingerprint of red noise.

Thus, we choose to apply a more specific tool to the analysis of our short record of residuals, namely the so-called Monte Carlo singular spectrum analysis (MCSSA): see Allen and Smith (1996) for a specific reference and Ghil et al. (2002) for a more general review. This method is particularly useful for the analysis of short geophysical time series and can help to distinguish between red noise and signals of hidden dynamics. This “eigenvalues” method is quite complex and we refer to Allen and Smith (1996) and Ghil et al. (2002) for a wide explanation of its theoretical foundations. Here, we apply it to our time series of residuals and discuss about the results shown in Fig. 5.

In Fig. 5, the vertical bars represent the confidence limits for a red noise signal “compatible” with our time series. They are estimated running a Monte Carlo simulation, by using an AR(1) process whose parameters are extracted from the original time series of residuals: this is a usual way of acting when an a priori knowledge of the process is unknown. Furthermore, the SSA covariance matrix of our series is projected onto the eigenbasis of red noise generated by the red noise parameters cited above, thus giving the projected eigenvalues in this new basis. In Fig. 5, the black stars properly represent these projected eigenvalues. Both confidence limits and projected eigenvalues are plotted against the dominant frequencies of the red noise eigenbasis.

In Fig. 5, even if the great majority of black stars lies inside the confidence limits, some points exceeding these limits suggest the presence of components different from red noise, so probably due to some dynamics.

In short, no undoubted conclusion can be reached by our analysis of residuals. Besides, it is well known how difficult is to distinguish between noise and chaotic dynamical signals in short time series. The most powerful tool used here (MCSSA) shows that some dynamics can be hidden in these residuals, so suggesting the presence of further dynamical elements that force the climate system, neglected in the present study. Nevertheless, the large amount of variance explained by our model leads to be confident that the major elements of the climate dynamics have been considered here and that only dynamical elements that act at a second-order stage have been neglected in our study.

5. An influence analysis at regional scale

In this regional case study, we want to analyse the fundamental elements that drive the temperature behaviour at a regional scale, with the same strategy used in the previous section.

It is well known that a peculiar teleconnection has been recognised between NAO and patterns of temperature and precipitation in Europe, especially during winter. For example, NAO index correlates linearly quite well with winter temperatures: sometimes a so-called extended winter (December–March) is considered in these studies, as well as in the present analysis.

In a previous paper (Pasini et al., 2003b), we found that a neural model is able to estimate temperature values at regional and local scales from data of NAO index and its performance is better than that of linear models. It is worthwhile to stress that this result has been obtained simply by starting from the characteristic features of correlative law-finder of a neural network model and from data about NAO index only.

Here, instead, we follow the approach described in the previous section, in order to assess the relative influences of global forcing and a regional circulation pattern like the NAO on temperatures behaviour, by considering the case study of an air temperature record during extended winters (since 1860) on Central England, derived from the more complete CET time series (see Fig. 6).

The first attempt at reconstructing the winter CET series has been done by use of a neural network fed by both natural and anthropogenic global forcings as inputs. The result of this reconstruction is very poor, with very low linear correlation coefficient in the analysis of observed temperatures versus estimated temperatures and quite high values of the mean absolute error (MAE). In Fig. 7 the absolute values of residuals (estimated temperatures − observed temperatures) and values of MAE are shown for the three cases considered here.

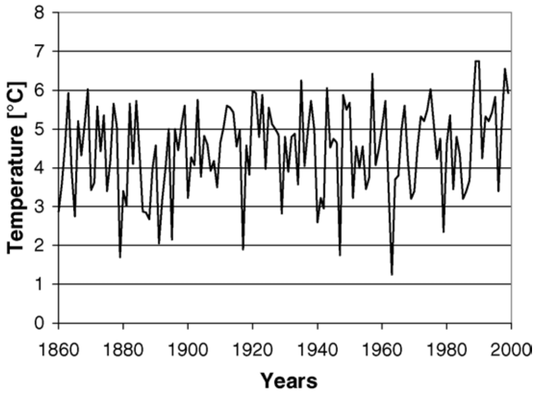

Fig. 6. CET time series during extended winters (December–March).

This first very clear result shows that global forcings have a very little influence on the behaviour of temperatures in the Central England. Furthermore, it seems quite plausible, if we consider that the extended winter CET series in Fig. 6 shows a small increasing linear trend but no clear sign of change in time, unlike what happens at the global temperature behaviour, which is highly correlated with global forcings, too.

In this situation, the next obvious step consists in considering the influence of the NAO phenomenon on these regional temperatures. In doing so, we build up two networks: the first one is trained by using a seasonal NAO index related to extended winter (built up as the average of monthly NAO indices related to December–March) and has a simple topology with one input; the second one allows the merging of data about both global forcings and NAO index and, obviously, is endowed with five inputs. The results of these two attempts at reconstructing the CET series are quite similar. In particular, the values of linear correlation coefficient (estimated T versus observed T) are both around 0.72–0.75.

If now we look also at Fig. 7(b) and (c), we can appreciate: (i) the good reconstruction performance of the two neural models that use NAO data as inputs; (ii) the similar low values of MAE in these two cases. However, we stress that the values of linear correlation coefficients in these successful cases of regional reconstruction are lower than in the analogous situations of previous global case study. If we consider the enhanced inter-annual variability of climate at regional scale (as

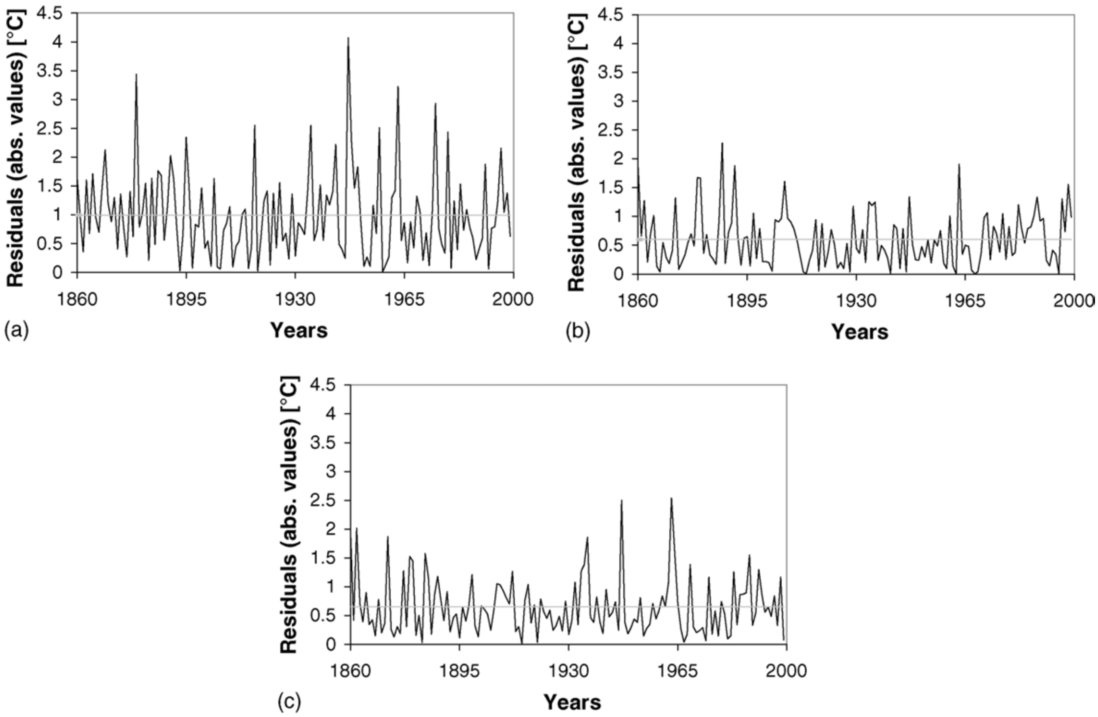

Fig. 7. Absolute values of residuals (neural estimations − winter CET observations) and MAE value (horizontal gray line) when networks have been trained by inputs related to: (a) global (natural + anthropogenic) forcings; (b) NAO only; (c) global forcings + NAO.

clearly visible in Fig. 6 when compared with Fig. 2), this is not a surprising result: now, at least partially, the not explained variance can reach higher values for this reason. Furthermore, we can suggest that the regional influence of some other circulation pattern, like the Arctic oscillation (AO), could be important for better reconstructing the temperature behaviour at this latitude and scale.

In summary, the present regional analysis shows that NAO can be considered as the driving force of temperature time pattern in Central England during extended winters, while global forcings do not influence directly this temperature behaviour. This evidence is very important for a correct estimation of climate in this zone, both in past reconstructions and in prediction of future scenarios. In particular, this importance is two-fold: first of all, we expect that only regional dynamical models that are able to correctly describe the NAO phenomenon have a chance to give reliable reconstructions and predictions of the climate features in this region; secondly, statistical downscaling models have to consider NAO as a fundamental element for the determination of a reliable climate scenario on this zone.

6. Conclusions and perspectives

In this paper, we have presented the application of a neural network model for the evaluation of the relative importance of global physical–chemical forcings and circulation patterns on the behaviour of temperatures at global and regional scales. This non-dynamical approach allows us to obtain simple assessments about the influence magnitude of different hypothetical causes on the same effect (here, temperature changes) in a complex system.

At global scale, as suggested also by the use of dynamical models (AOGCMs), we are able to reconstruct the global temperature behaviour only if we take the anthropogenic forcings into account. Furthermore, we are able to recognise the influence of ENSO in better catching the inter-annual variability of our global time series of temperature.

At a regional scale, the recognition of the major influence of NAO on the CET time series during extended winters appears very important. In general, our results can be used in order to identify the fundamental elements for obtaining both successful dynamical regional models and reliable statistical downscaling of AOGCMs, not only on climate reconstructions in the past, but also on future scenarios.

As a perspective of further work, we want to stress that our neural network modelling activity can be used as a phenomenological tool for obtaining preliminary assessments on the magnitude of influence of several other possible causes of climate change at distinct scales and in other regions here not explored. For instance, it will be certainly fruitful: (i) to consider an extension of inputs in the neural model to other kinds of forcing (e.g., through insertion of data about changes in land use and deforestation) and to other circulation patterns or oscillations known in the climate system; (ii) to apply our method to other regions of the world; (iii) to extend further our treatment to the reconstruction of precipitation regimes.

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